Leveraging IIoT for Machine Self-Healing While the Pool of Experienced Maintenance Mechanics Slowly Evaporates

Frederick C. "Chris" Lang
Graduate Student – Old Dominion University
Norfolk, VA
flang001@odu.edu

ABSTRACT

Keeping industrial manufacturing machinery healthy in a world with an ever-evaporating pool of experienced maintenance mechanics will become a dire issue if current trends continue on the same trajectory. The lack of knowledgeable mechanics will force industry operators and owners to seek non-traditional methods for machine maintenance and machine health. One such avenue will be to leverage the use of the Industrial Internet of Things (IIoT) and the analysis of Big Data in concert with machine level controllers so that machines will be able to predict and perform self-healing measures in the absence of skilled maintenance personnel. Methodology for the experimental sections of this paper will use Big Data analysis using the time-series to Frequency Domain transformation to help predict the useful life of a machine's bearings via sensor data gathered using IIoT systems. Local machine controllers will be needed to configure the operational data for the equipment that is monitored per the Original Equipment Manufacturer (OEM) specifications. The scope of work will encompass the use of Exploratory Data Analysis (EDA), data cleansing, and data analysis to model the process in which a machine can self-diagnose bearing function to determine whether the machine can apply self-healing techniques or send alerts for human intervention. Findings and main results will be seen in the arena of continued operation and availability of the machinery in the absence of a trained work force.

ABOUT THE AUTHOR

Frederick C. "Chris" Lang has a B. S. in Engineering Technology from Old Dominion University with a concentration in Automation Control Systems. He is currently in his last semester as a Masters candidate for a M. E. in Systems Engineering (MESE). His career background consists of over 30 years of electrical and automation engineering in industrial manufacturing and OEM environments.

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INTRODUCTION

In a statement by Tim Bleich, the president of the industrial recruiting company, Vector Technical, Inc., according to Barry (2018), "There's this tremendous transfer of knowledge that needs to happen but we don't have the people to get it done". This sentiment is repeated throughout the industrial arena. As the pool of skilled maintenance workers declines, the manufacturing industry is picking up. Also told by Barry (2018), where he notes Roger Sustar, owner of Fredon Corporation, a manufacturing plant for a wide variety of machine parts; "Everybody is seeing a big upswing in work and that work is causing us to try to keep things moving". The decline in experienced maintenance workers will force plant owners, plant operators and Original Equipment Manufacturers (OEMs) to outfit existing and newly constructed machinery with systems to ensure that the machines will keep operating in a healthy manner in the absence of qualified technicians. Part of these systems would implement Condition Based Maintenance (CBM). The CBM portion allows real-time monitoring of the equipment's devices via various types of sensors. This portion, in addition with mathematical modeling tools and local control systems will allow the machine to diagnose and apply data realized solutions on-the-fly to help with the machine health.

This paper will recommend a bifurcated hybrid approach to machine health and monitoring. One aspect will utilize the IIoT scheme for gathering high volume and complex sensor data. For instance, the high volume and rate for an accelerometer to measure the vibration rate of a bearing would be handled by data analytic software on either a local server or cloud via IIoT. The industrial internet as defined by Bruner (2013) is "this union of software and big machines — what you might think of as the enterprise Internet of Things, operating under the demanding requirements of systems" (p. 1). The second aspect will employ the proficiency of the local machine control platform for less data intensive prognostics and sensor input. The latter notion is echoed by Wilber (2018), where he writes "Device-level analytics have also gotten smarter. Rather than simple timers calculating a point of failure, algorithms run on devices to predict failure and adapt these predictions based on surrounding conditions". However, many devices, such as bearings, are mechanical and do not have an embedded electronic analytical calculating infrastructure. To accomplish this characteristic, sensors will need to be field installed on existing machines or installed by the OEM on the factory floor. The sensor(s) will then be connected to the machine's current controller platform.
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EXPLORATORY DATA ANALYSIS

The bearing dataset is from the accelerometers mounted on four bearing casings which held a spinning shaft at a constant 2000 rpm. The center two bearings are radially loaded with a 6000 lb load. The setup can be seen depicted in **Figure 1** below.

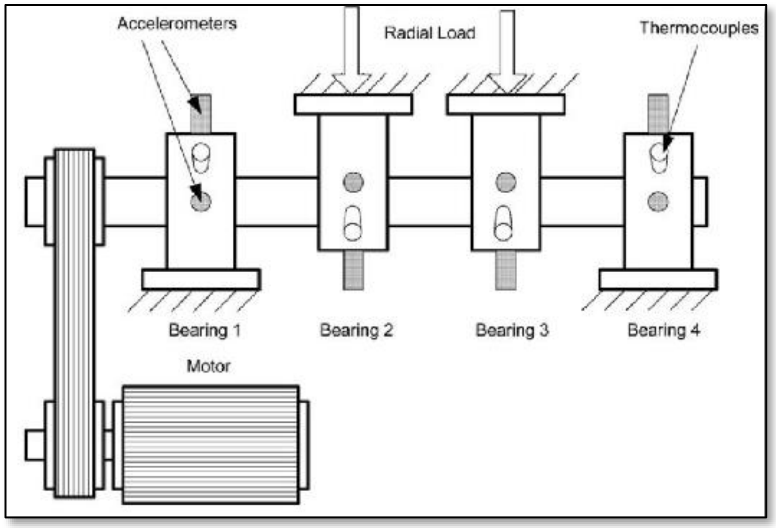
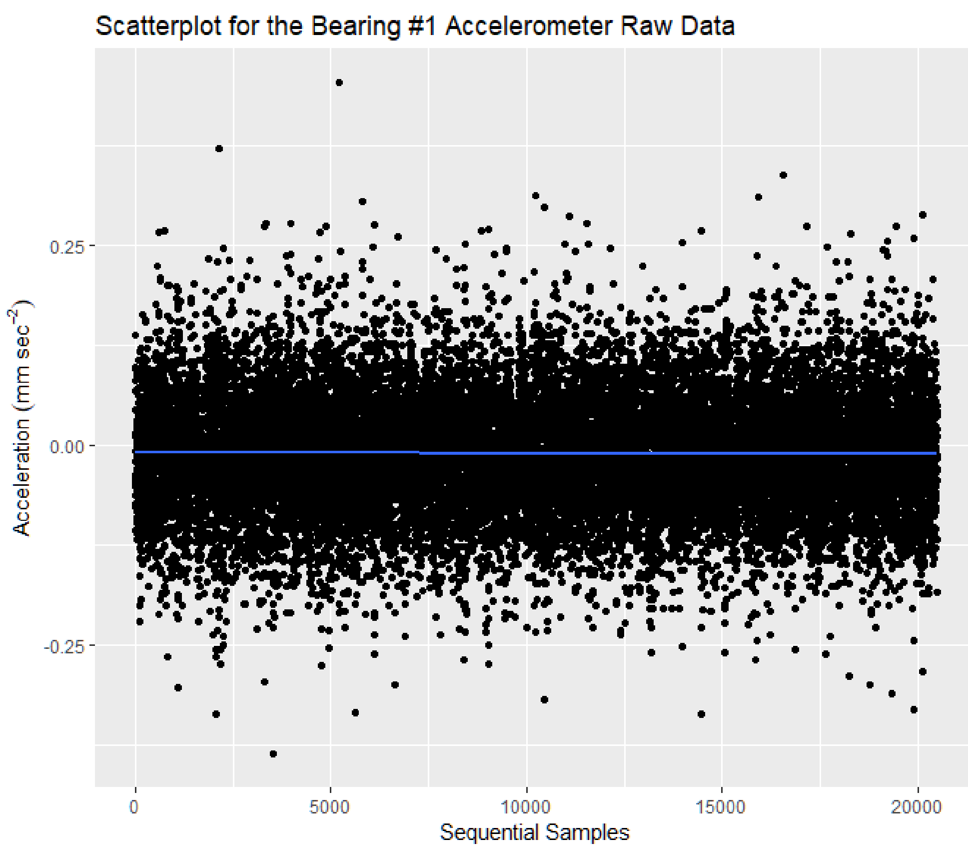


Figure 1 Test Bed Setup (Adapted from Tobon-Mejia et al., 2011)

The dataset used in this paper will focus on that of bearing #1 from the second test-to-failure found in (Lee et al., 2007). The complete dataset contains the acceleration data from one of the accelerometers affixed to each bearing mount. The sensors were sampled at a rate of 20kHz for one second at ten-minute intervals. The test covers a time range from 02/12/2004 10:32:39 to 02/19/2004 06:22:39. This yields a dataset of approximately 20,152,320 records. This is because each one-second interval of sampled data contains roughly 20,480 sensor scans. A plot with a smoothing line of the first one-second interval of the raw data using RStudio® is found in **Plot 1** below.



Plot 1 Raw Data Plot of First One-second Interval

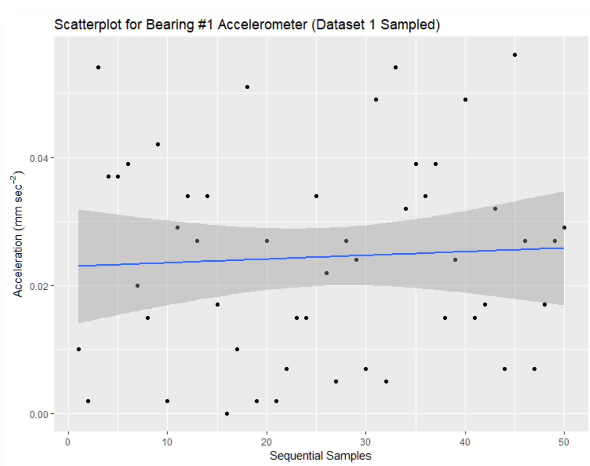
As can be seen in the plot above, there is a huge amount of data that can be filtered out of the set that is not useful and extraneous. A table of the summary of the accelerometer mounted on bearing #1 for various datasets at the indicated stages of the test can be found in **Table 1** below.

Table 1 Summary of Various Datasets for the Accelerometer on Bearing #1

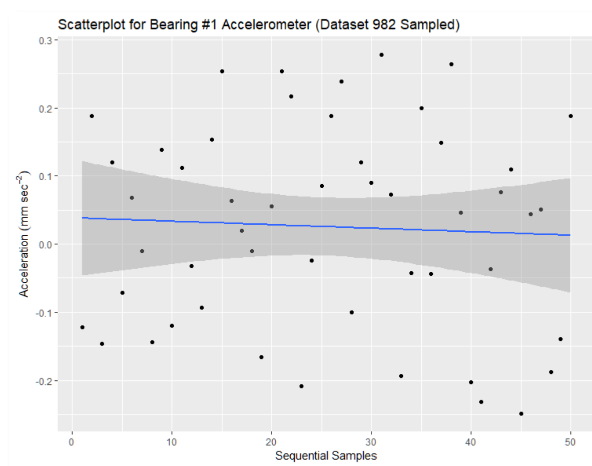
	Dataset 001 (Begin)	Dataset 492 (50%)	Dataset 590 (60%)	Dataset 688 (70%)	Dataset 787 (80%)	Dataset 885 (90%)	Dataset 982 (Fail)	Dataset 983 (End)
Min.	-0.3860	-0.36900	-0.422000	-0.547000	-0.53500	-0.862000	-3.696000	0.000000
1st Qu.	-0.0590	-0.05100	-0.061000	-0.066000	-0.06600	-0.081000	-0.261000	0.002000
Median	-0.0100	0.00000	-0.020000	0.000000	-0.00200	0.000000	0.020000	0.002000
Mean	-0.0102	-0.00129	-0.002903	-0.002171	-0.00206	-0.002694	-0.001703	0.001857
3rd Qu.	0.0370	0.04900	0.056000	0.061000	0.06300	0.083000	0.281000	0.002000
Max.	0.4540	0.37600	0.410000	0.518000	0.48600	0.933000	3.501000	0.005000

DATA CLEANSING

The datasets were then cleaned up and the superfluous data was filtered out using the data captured from the 1st to the 3rd quantile. The dataset was also sampled from the filtered set to reduce the sheer number of points in the set to one hundred samples. Plots of the sampled datasets for the first second of the test and the failure intervals are found in **Plot 2** and **Plot 3** below.



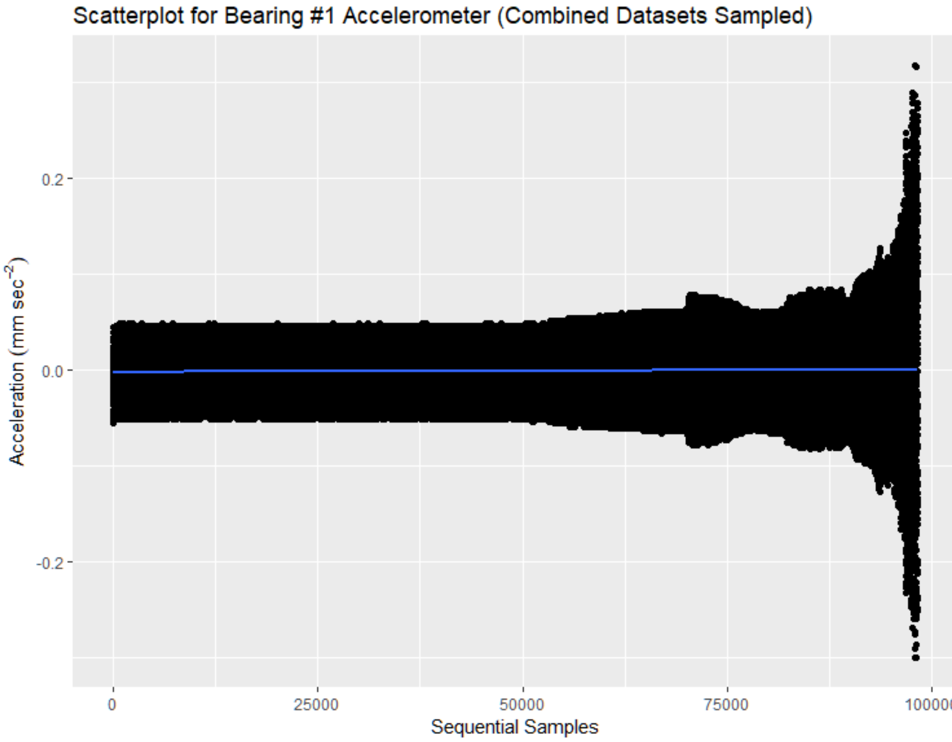
Plot 2 Sampled Plot of the First One-second Interval



Plot 3 Sampled Plot of the Failure Interval

ANALYSIS OF CLEANSED DATA

The nine hundred and eighty-four separate datasets were then combined into a single dataset using Windows® PowerShell® so that an overall picture can be seen of the complete test. From the plot in **Plot 4** it is easy to see that as the test progressed to failure, the acceleration of the accelerometer increased significantly in both the positive and negative direction. Using this data one can predict when a bearing is approaching its failure "zone".



Plot 4 Plot of the Combined Sampled Datasets

Looking over the sampled dataset in **Plot 4**, one can see that the magnitude of the acceleration steadily trends to increasing as time moves forward. This trend starts around the 60% mark of the test. One accepted method of analyzing a time-series dataset is by transforming the set into the frequency domain. This allows one to see the amplitude of the accelerations in relation to time elapsed.

According to Shumway & Stoffer (2017), "the concept of regularity of a series can best be expressed in terms of periodic variations of the underlying phenomenon that produced the series" (p. 167). To that end, and due to the large quantity of redundancies, the Fast Fourier Transform (FFT) can be used to quickly compute the amplitudes of the dataset over a time-series. The equation for the FFT is seen below in equation 1.
.

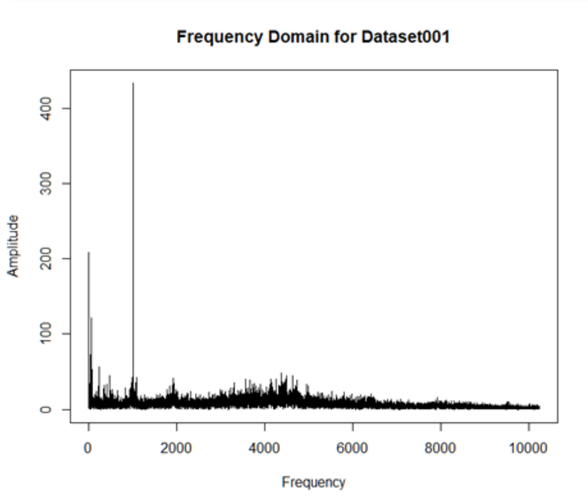
$$|d(j/n)|^2 = \frac{1}{n}\left(\sum_{t=1}^{n} x_t cos\,(2\pi tj/n)\right)^2 + \frac{1}{n}\left(\sum_{t=1}^{n} x_t\, sin(2\pi tj/n)\right)^2 \tag{1}$$

The implementation of the FFT for the first dataset of the accelerometer on bearing #1 in R can be seen below:

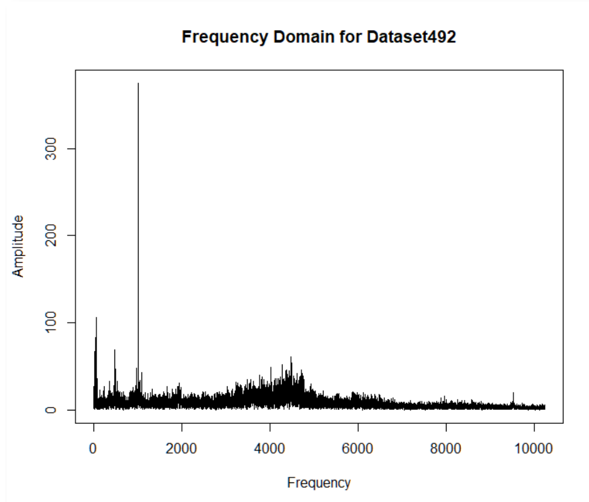
```
dataset001.fft <- fft(Dataset001Raw$V1)
dataset001.amp <- Mod(dataset001.fft[1:(length(dataset001.fft)/2)])
dataset001.freq <- seq(0, 10240, length.out = length(dataset001.fft)/2)
plot(dataset001.amp ~ dataset001.freq, , main="Frequency Domain for Dataset001",xlab  = "Frequency", ylab = "Amplitude", t = "l")
```

One can see in **Plot 5** that the amplitudes are relatively below fifty for the majority of the plot with a few anomalies. **Plot 6** reveals that the amplitudes are starting to creep above the fifty mark around the hallway point of the bench test.

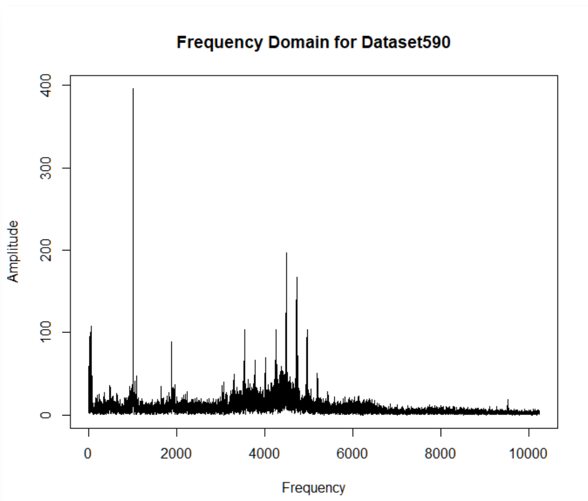
Further along, in **Plot 7**, many amplitudes above the one hundred mark can been seen at the 60% mark of the bench test. This indicates the beginning of the degradation of the bearing. The degradation of the bearing can continue to be tracked into **Plots 8, 9,** and **10** as the bench test progresses.



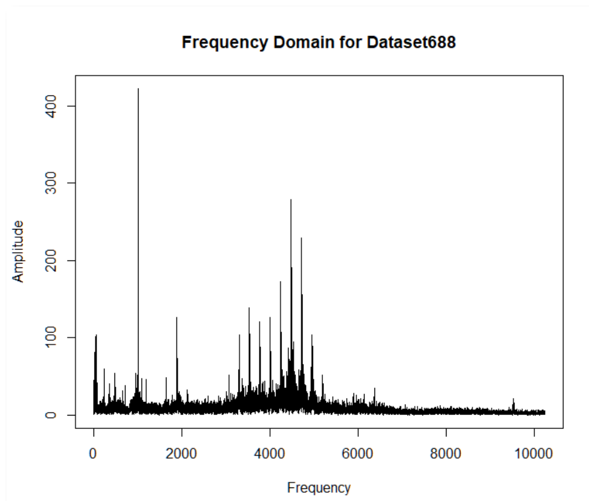
Plot 5 Frequency v. Amplitude Plot for First Data Segment



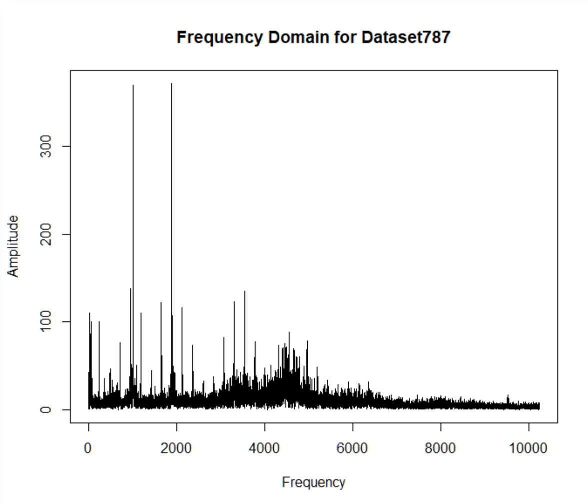
Plot 6 Frequency v. Amplitude Plot for 50% Data Segment



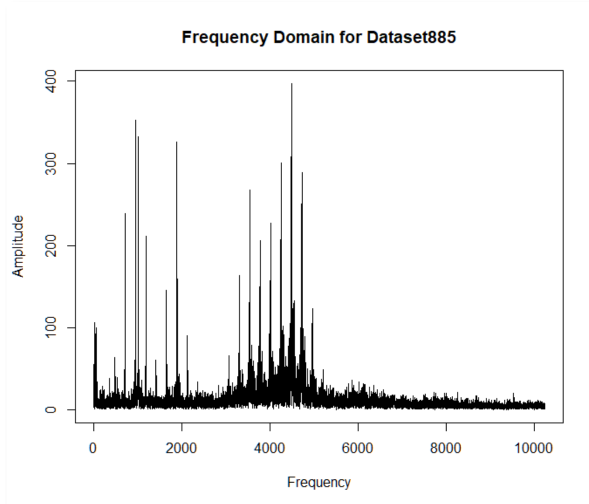
Plot 7 Frequency v. Amplitude Plot for 60% Data Segment



Plot 8 Frequency v. Amplitude Plot for 70% Data Segment

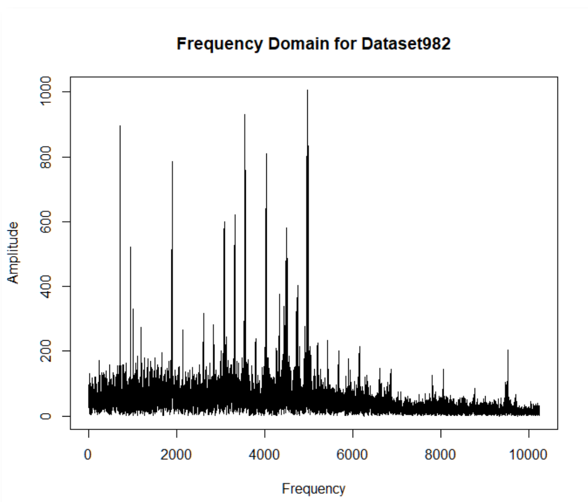


Plot 9 Frequency v. Amplitude Plot for 80% Data Segment

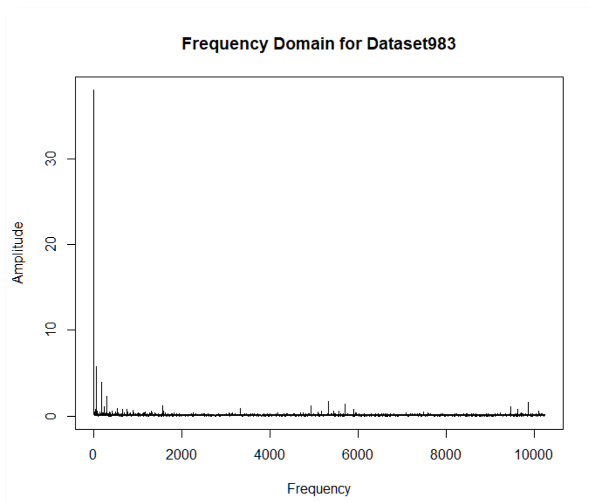


Plot 10 Frequency v. Amplitude Plot for 90% Data Segment

The failure of the bearing can be seen in **Plot 11** as the amplitude soars to one thousand. This information can be used to determine when to send an alert to the system that the bearing is danger of failing. This can be done by determining the threshold in which the number of counts of amplitudes above the one hundred mark is exceeded. For instance, when the number of times the amplitude one hundred, 60% of the bearing life has been used. Conversely, only 40% of the bearing life remains. Finally **Plot 12** depicts the amplitudes of the machine after failure shutdown.



Plot 11 Frequency v. Amplitude Plot for Failed Bearing Data Segment



Plot 12 Frequency v. Amplitude Plot for Machine Shutdown Data Segment

LOCAL MACHINE CONTROL AND INTERACTION

This section will describe the interaction from the point-of-view of the machine controller and interfaces. There are many factors that contribute to bearing failure that is being used on a particular machine. A few of these are loading, lack of maintenance, and end of life usefulness. In order to monitor the parameters that are specified by the bearing manufacturer, the machine must have various sensors mounted on it. To completely monitor a bearing, one must know at a minimum:

- Temperature
- Revolution rate
- Total number of revolutions
- Vibration acceleration

By tracking these variables and storing them in a database, the machine can compare them to records in a database to determine what type of maintenance is needed for the bearing. The amount of useful life can be monitored by the accelerometers via the IIoT and calculated off-site. The other parameters can also be stored off-site using IIoT and trending and other methods of machine health can be utilized.

CONCLUSION

This paper has shown the importance that the IIoT plays in gathering information and data to maintain machine health. By using FFTs to transform the time-series data into the frequency domain, the system can easily predict the remaining life of a piece of equipment and alert the system as to its current health status. The use of time-series trending and analysis of bearing mounted accelerators is invaluable for this purpose.

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